Enhancement of Primary User Detection in Cognitive Radio by Scattering Transform

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***Abstract*—The detecting of an occupied frequency band is a major issue in cognitive radio systems. The detection process becomes difficult if the signal occupying the band of interest has faded amplitude due to multipath effects. These effects make it hard for an occupying user to be detected. This work mitigates the missed-detection problem in the context of cognitive radio in frequency-selective fading channel by proposing blind channel estimation method that is based on scattering transform. By initially applying conventional energy detection, the missed-detection probability is evaluated and if it is greater than or equal to 50%, channel estimation is applied on the received signal followed by channel equalization to reduce the channel effects. In the proposed channel estimator, we modify the Morlet wavelet by using its first derivative for better frequency resolution. A mathematical description of the modified function and its frequency resolution is formulated in this work. The improved frequency resolution is required to follow the spectral variation of the channel. The channel estimation error is evaluated in the mean-square sense for different channel settings and energy detection is applied to the equalized received signal. The simulation results show improvement in reducing the missed-detection probability as compared to the detection based on principal component analysis. This improvement is achieved on the expense of increased estimator complexity, which depends on the number of wavelet filters as related to the channel taps. Also, the detection performance shows an improvement in detection probability for low signal-to-noise scenarios over principal component analysis-based energy detection.**

***Index Terms*—Channel Estimation, Cognitive radio, Scattering transform, Spectrum Sensing.**

I. Introduction

The foundation of the cognitive radio (CR) concept is a consequence of the absolute necessity to fulfill the requirements of high data rate communication [1]. This urgency is due to the natural limitaion of the scarce radio frequency. In CR systems, a cognition cycle, defined by the Federal Communication Committee (FCC), performs monitoring, awarness and management of the intended frequency band in order to provide dynamic spectrum access (DSA) [2]. Among different tasks performed by a CR system, spectrum sensing (SS) is one of the vital tasks in the cognition cycle that provides new paths to access locally unused frequency bands.

In accordance to its crucial importance, spectrum sensing confronts several challenges that limit the overall spectral efficiency [3], [4]. Normally, primary users (PUs) (i.e., licensed users) can claim their licensed frequency bands any time while CR users are operating on them. Hence, it is important to identify the presence of the PUs as fast as possible to keep the quality of service (QoS) offered to PUs. Therefore, selection of the sensing duration conducts a tradeoff between sensing accuracy and sensing speed. Also, the tradeoff between sensing time and thethroughput of the secondary user (SU) (i.e., CR user) is another issue in CR. These tradeoffs have been a great concern of many researches to find the optimum SS scenario [5], [6]. Another important challenge is to specify the sensing frequency which includes how often spectrum sensing should be performed. This design parameter depends on the temporal features of the PU in the intended band [4]. For instance, the sensing frequency can be relaxed if the PUs statues change slowy with respect to time. This is the case of the detection of white spaces of TV channels. However, this is not the case when the SU is checking spectral opportunities in the industrial, scientific, and medical radio band (ISM band). In such scenarios, the sensing frequency must be increased to protect the PU from any possible interference with SU.

The PU transmitter detection (PTD) methods are concerned with the monitoring of the PU activity in the at SU receiver. Depending on its design, CR systems apply one of the spectrum sharing techniques, namely: interweave, overlay, or underlay. The PTD techniques can be classified into blind-based and signal-specific-based techqniues [7]. The former techniques do not require prior information about the PU characteristics, whereas the latter implies the need for such information to detect the PU signal.

Many researches have been made to improve the PU detection taking into consideration the aforementioned challenges. For example, the authors in [8] use adaptive detection threshold so that the detection results are affected by the noise uncertainity. Further, the concept of principal component analysis (PCA) has been applied in [9] as a pre-processing step of the received signal before detection in which muliple antennas are used to improve spectrum sensing. For a fine detection accuracy, a modification has been made to the fast Fourier transform accumulation (FAM) algorithm in cyclostationary feature detection (CFD) to improve detection results [10]. Also, to provide reliablity of PU detection in a low signal-to noise-ratio (SNR) environment, scattering-based energy detection (ED) has been introduced in [11].

Among different challenges facing PU detection, we tackle the problem of missed-detection of a PU faded signal through a blind channel estimation using a scattering transform. The missed-detection problem occurs when the transmitted PU signal undergoes multipath fading due to the nature of the propagation channel. As a result, the signal components may add destructively such that the received signal strength becomes very weak. Eventually, despite the PU presence, the detector fails to detect it. Therefore, channel estimation and equalization are needed to reduce the multipath fading effect.

The main contribution of this manuscript is to estimate the channel between the PU base-station and the CR receiver using a scattering transform. The latter has the advantage of providing sparse representation of an analyzed signal [12]. In the proposed method, we modify the Morlet Wavelet (MW) function to gain high frequency resolution by using its first derivative. The modified function is called Morlet-Derivative Wavelet (MDW) which shows better frequency localization than the MW function. We use the MW since it is suitable for oscillatory signals. Better frequency resolution is important to follow the varaition of a frequency-selective channel. This technique is compared with PCA-based energy detection. In this work, energy detectors are used due to its simple implementation and reduced complexity as compared to feature-based detectors. Also, they are an appropriate choice if the complexity of the CR transmitter or receiver may be increased for performance improvement. The proposed method shows reduction of the missed-detection probability after applying the blind channel estimation and employing energy detection to the equalized received signal.

II. Representation of Signals by Scattering Transform

A scattering network analyzes a signal through complex modulus wavelet decomposition followed by an averaging process [13]. Through this iterative procedure, signals features are enhanced according to the signal projection of the chosen wavelet bases. In literature, the wavelet transform of a given signal $s(t)$ is a convolution operation using the operator $*$ with a low-pass filter $\phi(t)$ of a time support T, as well as convolving $s(t)$ with the dilated wavelet function $\psi(t)_{\lambda\in\Lambda}$ defining a band pass-filter, with λ being its center frequency and Λ is the set of all centers. A chosen mother wavelet is dilated and translated to analyze the signal, such that the dilated function is given by [13]:

$$\psi_\lambda(t) = \lambda\psi(\lambda t), \Psi_\lambda(\omega) = \Psi(\frac{\omega}{\lambda}) \tag{1}$$

where $\Psi_\lambda(\omega)$ is the Fourier transform of $\psi_\lambda(t)$. The wavelet transform (WT) of $s(t)$ is defined as:

$$WT\{s(t)\} = (s(t)*\phi(t), s(t)*\psi_\lambda(t))_{t\in\Re,\lambda\in\Lambda} \tag{2}$$

The complex wavelet transform modulus is then applied to remove the phases of all wavelet coefficients; Hence, we get:

$$|WT\{s(t)\}| = (s(t)*\phi(t), |s(t)*\psi_\lambda(t)|)_{t\in\Re,\lambda\in\Lambda} \tag{3}$$

Starting at the network root, the signal of interest is processed by low-pass filtering so the scattered output is given by [13]:

$$SC_0\{s(t)\} = s(t)*\phi(t) \tag{4}$$

To regain high frequency information, the complex modulus wavelet transform applied by the opertaor $U_1\{s(t)\}$ gives:

$$U_1\{s(t,\lambda_1)\} = |s(t)*\psi_{\lambda_1}(t)| \tag{5}$$

so averaging out the operator gives:

$$SC_1\{s(t,\lambda_1)\} = U_1\{s(t,\lambda_1)\}*\phi(t) \tag{6}$$

where $SC_1\{s(t,\lambda_1)\}$ is the first order scattering coefficients. These coefficients are computed with wavelets $\psi_{\lambda_1}(t)$ and Q_1 is defined as the number of wavelets per an octave in a constant-Q bank of filters. For any order an $M \geq 1$, the iterated wavelet modulus operator is given by [13]:

$$U_M\{s(t,\lambda_1,\lambda_2,...\lambda_M)\} = ||||s(t)*\psi_{\lambda_1}(t)|*\psi_{\lambda_2}(t)|*...|*\psi_{\lambda_M}(t)| \tag{7}$$

thus, the scattering coefficients at order M are defined by:

$$SC_M\{s(t,\lambda_1,\lambda_2,...\lambda_M)\} = U_M\{s(t,\lambda_1,\lambda_2,...\lambda_M)\}*\phi(t) \tag{8}$$

III. Channel Estimation by Scattering Transform

A. The System Description

The motivation behind the proposed technique is to improve the PU detection in a multipath fading environment by reducing the missed-detection probability. To accomplish this, the PU detection is first performed by applying an energy detection. This step is important to specify if the CR receiver has a missed detection probability greater than or equal to 50%. The system architecture is illustrated in figure 1. In general, the detection process is viewed as hypothesis testing problem which is defined mathematically by:

$$y(n) = \theta.x(n) + w(n) \tag{9}$$

where θ is a Boolean parameter indicating absence or presence of PU. $x(n)$ is the faded PU signal, $w(n)$ is the noise signal and $y(n)$ is the received signal by CR receiver. $\theta = 0$ means that we have H_0 hypothesis (i.e., PU is absent), otherwise $\theta = 1$, and H_1 is declared (i.e., PU exists). The energy of the received signal is measured and compared with a detection threshold. The test statistic for ED can by defined by [14]:

$$T.S[y] = \frac{1}{K}\sum_{k=1}^{K}|y_k|^2 \underset{H_0}{\overset{H_1}{\gtrless}} \gamma \tag{10}$$

where γ is the detection threshold and $T.S[y]$ is a random variable representing the energy of the K-fading components of the received signal. It follows a Gaussian distribution for K is large enough to invoke the Central Limit Theorem (CLT). If the ED declares H_1, the missed-detection probability, denoted by P_{MD}, is calculated [14]:

$$P_{MD} = Pr\{T[y] < \gamma|H_1\} \tag{11}$$

If it exceeds 50%, then the detector declares a missed-detection case. It means that there is a useful information in the received signal but it is very weak to be detected, so that channel estimation and equalization are employed to enhance the detection and the identification of a PU.

The proposed channel estimation technique is blind-based, which means that no pilot symbols or preambles are used to get the channel information. However, we apply a scattering transform using Morlet-Derivative Wavelet to analyze signal variations due to channel impairements. It is shown in [15] that scattering operators can be used to characterize a structure of the pitch filter of voiced and unvoiced sound waves. However, this characterization assumes a very narrow filter structure. In this work, we introduce th use of a first order scattering transform to estimate the fading channel coefficients through the modification of the Morlet function by using its first derivative in the wavelet analysis. This modification proves better frequency localization than the classic Morlet function. This localization is essential to capture the spectral variation.

The sparsity of scattering coefficients reflects essential variations and features in the signal through the layers of the scattering network. Moreover, since the signal is analyzed through a cascaded wavelet modulus and averaging process, the noise contribution is reduced through the network layers. This is due to the fact that the projection of the noise on the wavelet bases becomes very low. Needless to say, the choice of the mother wavelet function is important because it must resemble the intended signal to acquire its variation. In a passband communication, sinusoidal signals are used; Thus, the so-called Morlet-Derivative function becomes a suitable choice.

By getting the channel information,a channel equalization is performedd using the minimum-mean-square error (MMSE) method to remove the channel effect, and thus the equalized received signal is processed again by ED to accurately identify the PU [16] rather than modifying the threshold as mentioned in [8].

B. Mathematical Model

This section describes the mathematical model of the proposed channel estimation method. In general, the PU signal is a digital modulated analytic signal and the wavelet function used in the channel estimation step in is a complex analytic wavelet. Also, the multipath propagation channel is assumed to be a discrete, time-invariant, and frequency-selective Rayleigh fading channel [17]. A good example of such channel is the two-ray Rayleigh channel model or the three-ray Rician channel model if a strong line-of-sight (L.O.S) component exists. The general model for the received signal can be expressed in discrete-time representation by:

$$y(n) = \sum_k h(n;k)s(n-k) + w(n) \tag{12}$$

where $h(n;k)$ is the discrete channel impulse response given as a function of the discrete time index $n = 0,1,...N-1$, with N being the sequence length, and the time-shift k. The signal $s(n)$ is the digital modulated transmitted PU signal and $w(n)$ is the noise samples at the CR receiver. For time-invariant, linear, and frequency-selective channel, $h(n;k)$ is reduced to $h(0;k) = h(k)$. It means that, although the channel behavior does not vary with respect to time, each propagation path had different channel attenuation and path delay. So, $h(k)$ is defined as the time-invariant impulse response of the transmission channel to a unit impulse transmitted at time 0. To define $s(n)$ and $h(k)$, consider the passband representation of the transmitted signal $s(n)$ such that the real valued signal is expressed by:

$$s(n) = A(n)cos(2\pi f_c n + \phi(n)) \tag{13}$$

where $A(n)$ is the baseband signal with phase of $\phi(n)$. Since the analytic representation of signals is more appropriate in practical signal processing, we define $z(n)$ as the analytic version of the signal $s(n)$ that is given by:

$$z(n) = s_a(n) = z_r(n) + jz_i(n) \tag{14}$$

where $s_a(n)$ refers to the analytical version of $s(n)$ and $z_r(n)$ and $z_i(n)$ are its the real and imaginary parts, respectively. The real part $z_r(n)$ is the origional real-valued signal $s(n)$, whereas the imaginary part $z_i(n)$ is the Hilbert transform of $s(n)$. Accordingly, we can rewrite $s_a(n)$ as:

$$s_a(n) = A(n)[cos(2\pi f_c n + \phi(n)) + jsin(2\pi f_c n + \phi(n))] \tag{15}$$

so equivalently we obtain:

$$s_a(n) = A(n)\exp(j\phi(n))\exp(j2\pi f_c n) \tag{16}$$

From (13) we define the complex envelope of the analytic signal $s_a(n)$ by:

$$\tilde{A}(n) = A(n)\exp(j\phi(n)) \tag{17}$$

The time-invariant channel can be define by:

$$h(k) = \sum_{k=1}^{K} a_k \delta(k - \tau_k) \tag{18}$$

where a_k and τ_k are respectively the k^{th} path attenuation and the path delay of the propagation channel, and K denotes the number of propagation paths in the transmission medium. Thus, the received signal can be expressed by:

$$y(n) = \sum_k h(k)\tilde{A}(n-k)\exp(j2\pi f_c(n-k)) + w(n) \tag{19}$$

By assuming that the received signal model in (16) follows a two-path Rayleigh fading or three-path Rician fading model where the transmitter and the receiver are fixed (The case of transmission via a terrestrial microwave radio link). This received signal is processed by the proposed system at the SU receiver. The mathemaical description of the two processing stages following initial energy detection are described here.

1) ***Channel Estimation****:* An accurate detection decision depending on the channel estimates assumes the independent operation of signal detection and channel estimation or characterization of the underlying channel coefficients is impractical. To address this problem, the received signal will be processed by scattering transform to obtain the channel coefficients.

The Morlet wavelet function is a sinusoidal function windowed by a Gaussian function. To describe the Morlet-Derivative function, let us consider the complex analytic Morlet function $\psi_M(t)$ which is defined in time domain by:

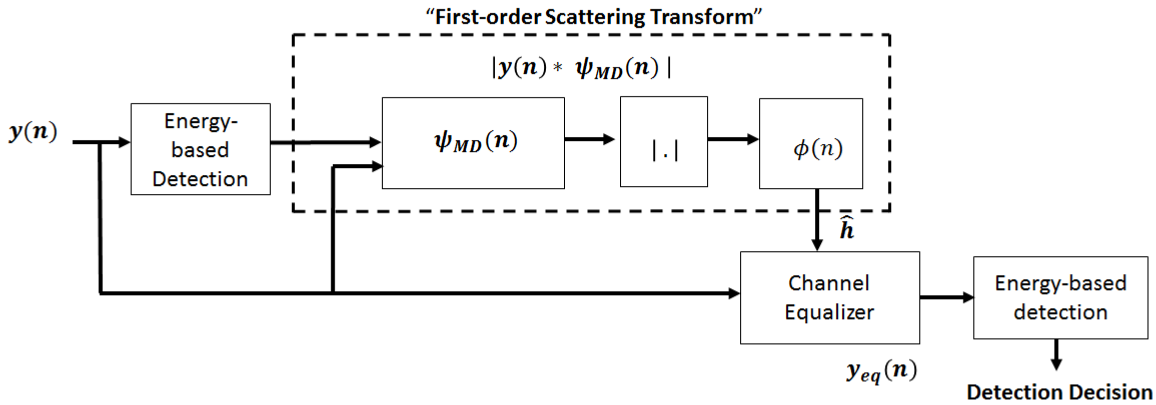

Fig. 1: A block diagram represents the hybrid blind signal detection method; $y(n)$ is the received PU signal, $y_{eq}(n)$ stands for the equalized received signal, $\hat{h}$ represents the estimated channel impulse response, and $\psi_{MD}(n)$ denotes the Morlet-Derivative function .

$$\psi_M(t) = [\exp(-j2\pi f_0 t) - \exp(-2\pi^2 f_0^2 \sigma^2)].\exp(\frac{-t^2}{2\sigma^2}) \quad (20)$$

where f_0 is the sinusoidal frequency,and σ represents the Gaussian spread in time. The Fourier transform of $\psi_M(t)$ is given by:

$$\begin{aligned}\Psi_M(f) =& \sqrt{2\pi}\sigma[\exp(-2\pi^2\sigma^2(f-f_0)^2) \\ &- \exp(-2\pi^2\sigma^2 f^2)\exp(-2\pi^2\sigma^2 f_0^2)]\end{aligned} \quad (21)$$

The Morlet-Derivative function is defined by:

$$\psi_{MD}(t) = \frac{d}{dt}\psi_M(t) \quad (22)$$

based on Fourier transform properties, (22) can be represented in the frequency-domain (FD) by:

$$\Psi_{MD}(f) = j2\pi f \Psi_M(f) \quad (23)$$

In literature, the Morlet wavelet function is an analytic wavelet that has good time resolution that is controlled by the time-spread of the Gaussian window but poor frequency resolution. Fig. 2 shows a comparison between the Morlet and the Morlet-derivative functions regarding frequency resolutions and support. From the figure, it is shown that the Morlet-derivative is admissible, compactly supported with better frequency resolutionn than the Morlet wavelet function.

To calculate the frequency resolution of the Morlet-Derivative function, we start by the general definition of the frequency resolution Δ_f that comes from:

$$\Delta_f^2 = \frac{\int_{-\infty}^{\infty} f^2 |\psi(f)|^2 df}{\int_{-\infty}^{\infty} |\psi(f)|^2 df} \quad (24)$$

to simplify the numerator of (24), we use of the following formula from famous Gaussian integrals that is given by:

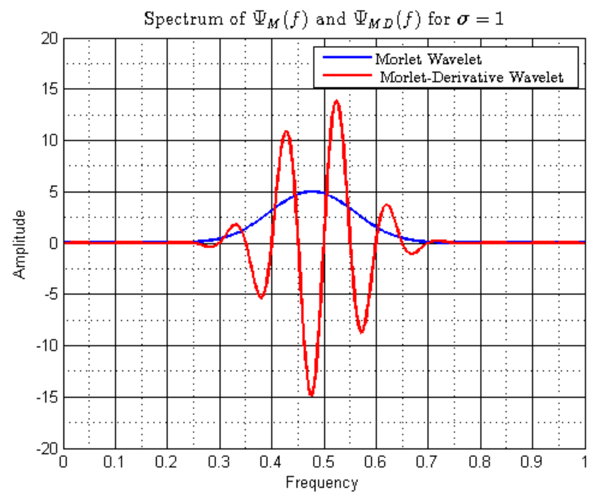

Fig. 2: Illustration of the frequency localization of the real Morlet and the Morlet-Derivative wavelet functions

$$\int_{-\infty}^{\infty} x^{-n}\exp(-ax^2+bx)dx = \sqrt{\frac{\pi}{a}}\exp(\frac{b^2}{4a})\sum_{k=0}^{n/2}\frac{n!}{k!(n-2k)!} \cdot\frac{(2b)^{n-2k}}{(4a)^n - k} \quad (25)$$

where $a = 4\pi^2\sigma^2$ and b are constants, and n and k are integers. By using (24) and (25), we obtain the expression for the frequency resolution of the Morlet-Derivative given by:

$$\Delta_f = \frac{f_0^2 + \frac{\sqrt{3}}{2a} - 0.5}{f_0 + \frac{1}{4af_0}} \quad (26)$$

where f_0 is the frequency of the MW.

To illustrate how to estimate the channel fading coefficients using scattering transform, let us recall the noisy received signal mentioned in (9) and get its discrete Fourier transform given by:

$$Y(l) = H(l)S(l) + W(l) \tag{27}$$

where l is the discrete frequency. For example, with three-path propagation model, we can modify (15) and get its discrete Fourier transform and substitute the result in (27) we get:

$$\begin{aligned} Y(l) = &(c_0 + c_1 \exp(-j2\pi k_1 l/N) \\ &+ c_2 \exp(-j2\pi k_2 l/N)) S_a(l) + W(l) \end{aligned} \tag{28}$$

where N denotes the sequence length of the received signal,$Y(l)$ is the received signal represneted in frequency domain, c_0, c_1 and c_2 are path attenuations, and the terms $2\pi k_1/N$ and $2\pi k_2/N$ are the relative frequencies indicating the phase shifts caused by the path delays. Also, the frequency domain of $s_a(n)$ is given by:

$$S_a(l) = N\tilde{A}(l - l_c) \tag{29}$$

where l_c is the discrete frequency of the carrier. To apply scattering transform in the frequency domain, the analytic signal must be processed by a constant-Q filter bank formed by dilating Morlet-Derivative wavelets. Refering to the three-path model, $\psi_{MD}(t)$ must be shifted in frequency such that the maximum wavelet frequency (i.e., the frequency value at which the wavelet peak appears) coincides with the relative shifted frequency of the related to multipath components. To illusrtate the sequence of operations, let us at first shift the Morlet-Derivative wavelet function with an angular shift frequency ω_{sh}, and then calculate the wavelet tranform of the received signal:

$$\begin{aligned} WT\{y(n)\} = y(n) * (\psi_{MD}(n) \exp(j\omega_{sh})) \\ + w(n) * \psi_{MD}(n) \exp(j\omega_{sh}) \end{aligned} \tag{30}$$

where ω_{sh} is given by:

$$\omega_{sh} = \frac{2\pi}{N}(m.l_{ch} - l_\psi) \tag{31}$$

where l_ch is the frequency location of the discrete channel impulse response ,m denotes a multiple integer of l_ch, and l_ψ is the maximum wavelet frequency.Here, we assume that the path delay is defined in terms of the symbol lengths. For instance, if the number of samples per transmitted symbol is about 20 samples, we can set the path delay k to be equal to 5 which means the path delay of a reflected signal component becomes half the symbol time. Denoting the symbol time by k_{sym}, the path delay in this case becomes equal to $0.5k_{sym}$. Thus, the frequency location of a multiptah component is $2l_{sym}$ for $l_{sym} = \frac{1}{0.5k_{sym}}$.

By getting the Fourier transform of (30), we get:

$$\mathscr{F}.\mathscr{T}(WT\{y(n)\}) = D(l) + \mathscr{W}(l) \tag{32}$$

where $\mathscr{F}.\mathscr{T}(.)$ is the Fourier transform. $D(l)$ and $\mathscr{W}(l)$ are the filtered faded PU signal with the wavelet function and the filtered noise spectrum, respectively:

$$D(l) = S_a(l)H(l)\Psi(l - l_{sh}) \tag{33}$$

$$\mathscr{W}(l) = W(l)\Psi_{MD}(l - l_{sh}) \tag{34}$$

The function in (34) can be reduced to $\sqrt{N_0/2}\Psi_{MD}(l)$ if the noise is a bandpass white Gaussian noise. Accordingly, scaled noisy version of the channel coefficients are given by:

$$\mathscr{F}.\mathscr{T}(WT\{y(n)\}) = c.\hat{H}(l) \tag{35}$$

where $\hat{H}(l)$ is the deduced channel coefficient and c is a scaling constant resulting from the wavelet peak and the ampitude of $S_a(l)$.

*2) **Channel Equalization**:* A perfect equalization process can reverse the distortion of signals transmitted by the channel. Zeroforcing (ZF) and Minimum-Mean-Square Error (MMSE) are examples of channel equalizers. ZF has the disadvantage of boosting-up the noise level at the equalziers output. As for the MMSE equalizer and to get the MSE we can integrate the power spectrum density and minimize it. We need to find the transfer function $G(f)$ such that the MSE is minimized. The error is given by [18]:

$$MSE = E|G(l)Y(l) - S_a(l)|^2 \tag{36}$$

accordingly, the required function is expressed by [18]:

$$G(l) = \frac{H^*(l)}{|H(l)|^2 + \frac{1}{SNR}} \tag{37}$$

where $H^*(l)$ is the conjugate of origional channel transfer function $H(l)$ and SNR is the signal-to-noise ratio.

IV. Numerical Results and Analysis

This section illustrateS the detection improvement gained through performing channel estimation as compared to PCA-based detector. In this work, energy detection is used to test the efficiency of the proposed method as compared to PCA-basd ED. In the simulations, the PU signal was considered as a bandpass BPSK signal with carrier frequency of 20 Hz and sampling frequency of 10 Hz. The total received sequence

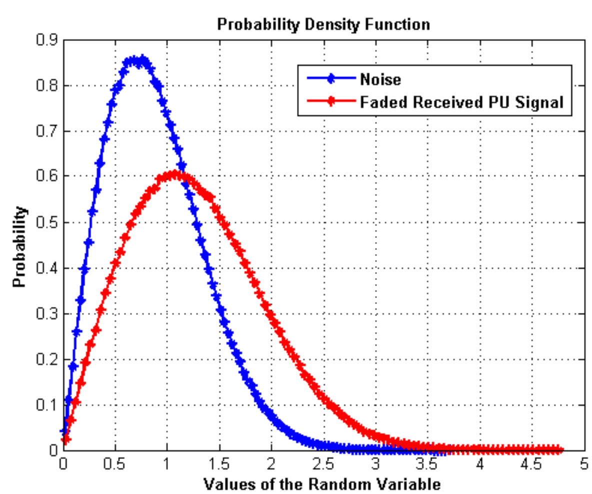

Fig. 3: Distribution of Noise and Faded PU signal with 10-Taps Channel

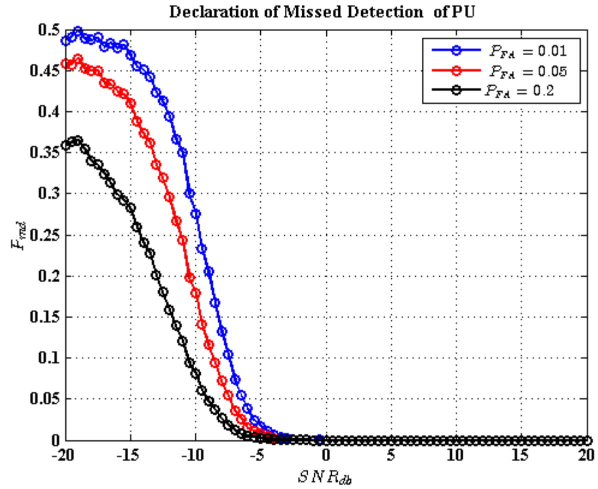

Fig. 4: Missed detection probability PCA-based ED with 5-taps channel

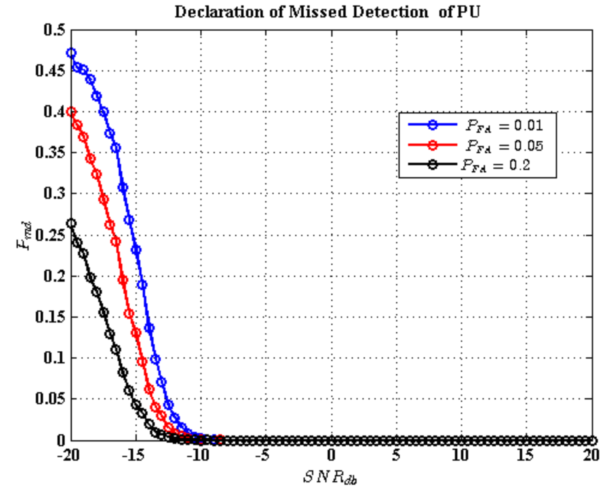

Fig. 5: Missed detection probability PCA-based ED with 10-taps channel

length is 1000 samples such that data are transmitted in 100 blocks each consists of 10 samples. The propagation channel is a time-invariant, fixed, frequency selective Rayleigh fading channel. In order to apply the initial energy detection process, we must firstly specfiy the distribution of the test statistic defined in (10). By using an histogram to estimate the channel distribution, for 5-taps and 10-taps channels, the test statistic is showed to follow a Gaussian distribution. Accordingly, the noise variance is also estimated by using an histogram and it was used to determine the detection threshold as shown in fig. 3 where we have faded PU signal with 10-taps Rayleigh channel as well as the noise distribution.

Further, an imposed noise is assumed to be a circular symmetric complex Gaussian (CSCG). Simulations for ED and channel estimation are conducted for specifically 5-taps and 10-taps channel settings. The tap-delays are expressed in terms of the number of samples per data block such that the maximum delay is equivalent to 8 samples. To evaluate the PCA-based ED perfomance, MonteCarlo simulations have been conducted over 10^6 iterations and evaluate the missed detection probability for the two fading channels. This is shown in fig. 4 and figure 5.

By applying channel estimation using the proposed method, the mean-square error of the channel estimate was evaluated as shown in fig. 6 for 5,7 and 10 taps channel settings. As the number of taps increases the number of wavelet filters increases as well which increases the complexity but the performance is improved as the MSE is decreased. To avoid boosting up the noise when ZF is used as a channel equalizer, we applied energy detection again to the equalized output and evaluate the missed detection probability, see fig. 7.

It is obviuos from fig. 7 that the missed detection probability is reduced after using channel estimation by scattering transform although the number of required filters increases with the number of the channel taps. Therefore, the channel

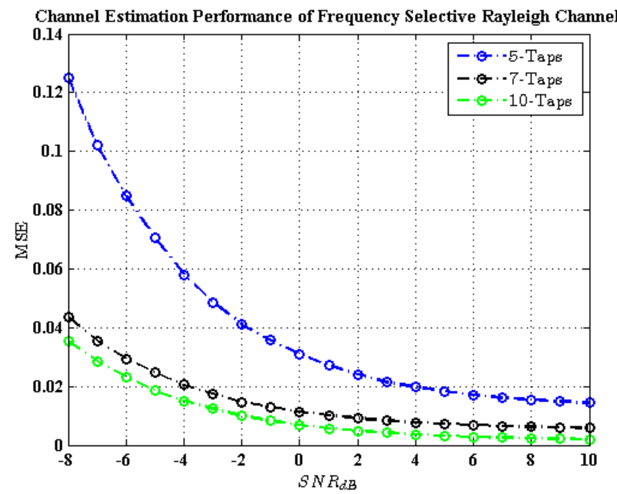

Fig. 6: Mean-square error of channel estimaion with various SNR values

estimation can increase the CR receiver complexity, but the ED shows improvement over PCA-based ED with increased number of antennas. Finally, the detection probability after for using channel estimation becomes higher than the one of PCA-based ED witth a low SNR. Indeed, a hidden signal due to faded amplitude can be better detected. Thanks to the channel estimation part, see fig. 8.

V. Conclusion

In this manuscript, blind channel estimation by scattering transform is proposed to enhance the PU detection scenario in CR.. In the proposed method, we modified the Morlet wavelet function by using its first derivative for better frequency resolution and formulate a mathematical description for the frequency resolution of the Morlet-Derivative wavelet function. This function is used as the filtering function in

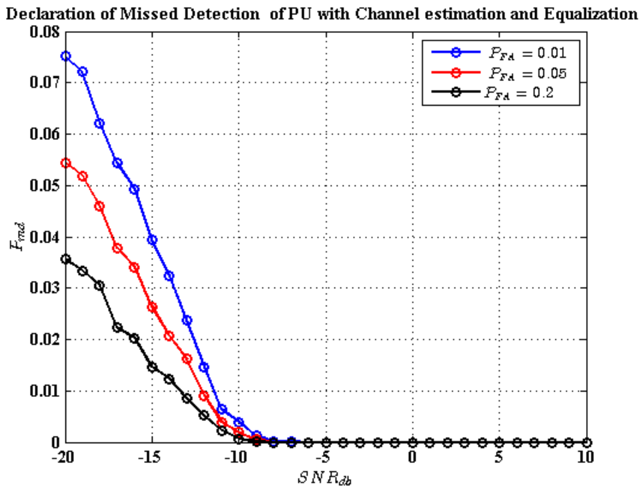

Fig. 7: Missed detection probability for variuos signal-to-noise ratio for 5-taps channel after channel estimation and equalization

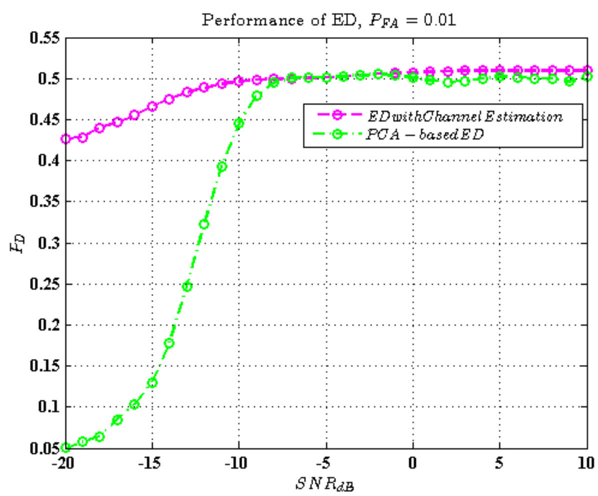

Fig. 8: Detection performance for using channel estimation as opposed to PCA-based ED for 5-taps channel

the constant-Q wavelet filter bank in the scattering transform. We intially performed ED and then evaluated the missed-detection probability, if this probability is greater than or equal to 50%, channel estimation is applied such that the first order scattering coefficients reveal the discrete channel impulse response. Following this step, a MMSE channel equalization is performed and energy detection is applied to the equalized received signal. The results show an improvement in reducing the missed-detection probability after applying the channel estimation over PCA-based ED despite the increased complexity. By applying the channel estimation, the detection performance is also improved with low SNRs. As for future work, one planning to apply feature detection to specifically identify the PU and improve the overall performance of spectrum sensing.

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